Should You Swipe Right? Two-Sided Search in Swipe-Based Dating Applications

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Abstract

In today's love market, swipe-based dating apps such as Tinder or Bumble have a well-established presence, but novel platform features can add significant complexities to the user's search problem in ways that have gone largely under-studied in existing literature. This paper formulates a game-theoretic model of two-sided search within swipe-based dating apps, along with an appropriate equilibrium refinement. Using numerical methods, I approximate equilibria at the steady-state and perform comparative statics on various model parameters that help explain stylized facts observed in aggregate Tinder data. Finally, agent-based simulations are used to analyse off-path dynamics and discuss how exogenous platform features can be set in a socially-efficient manner.

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1 Introduction

It is widely acknowledged that the search for love is a complex social phenomenon, but in today's world, swipe-based dating applications (SBDA's) seem to only make it trickier. These platforms, exemplified by Tinder, Bumble, or Hinge, provide a gamified way of browsing through potential romantic partners by swiping through a stack of suggested candidates to indicate likes or dislikes for these, one profile at a time. In the search and matching literature, settings like these fall under the category of decentralized two-sided matching markets with online search (Kanoria and Saban, 2021), emphasising three main characteristics. Firstly, that both sides of the market are comprised of decision-making agents undertaking a process of search. Secondly, that matches occur as outcomes of independently-determined search decisions, rather than through a centralised algorithm. Thirdly, that romantic suggestions are presented in an online manner to users, stressing the importance of sequential rationality given that it is not possible to revert interactions with previous candidates. These apps differ widely from traditional dating sites where users are centrally and statically matched (such as match.com or eHarmony), but have come to dominate the modern love market, with Tinder alone boasting 75 million monthly active users and 9.6 million paid subscribers as of 2021 (Business of Apps, 2022).

From a theoretical standpoint, search within SBDA's induces several additional complexities due to platform-specific features, such as swiping caps, asynchronicity, and directed search algorithms. These impose non-trivial constraints on the way utility-maximising agents strategise their search process, but they have been sparsely studied in the economics literature due to the relative novelty of these platforms. Overall, the prevalent role of SBDA's in shaping modern romantic interactions and their largely understudied nature motivates many different questions. Nevertheless, exploring these demands a fundamental understanding of how users make decisions in these platforms: to put it simply, *when should a utility-maximising user swipe right?*

This dissertation will explore the above within an SBDA platform setting, where agents with heterogeneous preferences on both sides of the market search simultaneously for multiple romantic partners. Crucially, I focus on explaining (what I refer to as) the 'Fast-Swiping Males' puzzle: that is, the empirical observation that men in SBDA's respond with significantly higher swipe rates and face considerably worse matching outcomes than women. This phenomenon has been both a subject of empirical research (Tyson et al., 2016) and an extensively documented discussion point within mainstream media (Vice News, 2016; The Washington Post, 2016) and yet, in spite of this, a significant gap persists within the literature for a discussion of this through a theoretical lens [1]. Such analysis would add significant value since the potential causes of this phenomenon (user patience, differential preferences, and strategic dominance) are all systematically endogenous with one another, thus demanding a rigorous model that can isolate these individual effects and capture their propagation across the SBDA market. Fundamentally, I show how gender imbalances within the platform (which arise due to several exogenous factors) can explain swipe rate disparities within the platform and, expanding on this, I model a possible intervention where the swiping cap ratio between sexes can be set in a socially-efficient manner.

This work presents two main contributions to existing literature on the topic. Firstly, it constitutes one of a handful of attempts to model the market configurations arising

[1] Among the surveyed literature, perhaps the only partial examination of this phenomenon is provided by Kanoria and Saban (2021)

within SBDA's, which is unsurprising due to the novelty of these platforms, but important given their current social relevance. Furthermore, this work distinguishes itself by considering the impact of swiping caps in the market, both as a constraint within the agent's search problem and a potential market correction mechanism. Finally, this work provides an interesting case study for the use of computational methods within game theory, a field that has traditionally emphasised pure mathematical analysis. By pairing a rigorously-formulated model with numerical approximations and agent-based simulations, this dissertation exemplifies how the two approaches, rather than being mutually exclusive, can be jointly employed to explore complicated questions, as computational methods enable quick explorations that can serve as a stepping stone towards formalising mathematical arguments.

The remainder of the paper is structured as follows. In Section 2, I outline the theoretical framework for the model developed in this paper, and derive necessary conditions for both the system steady state and the agent best-response correspondences. In Section 3, I present a refined definition for the steady state equilibrium of the model and perform computational comparative statics on several parameters, with the aim of replicating stylized empirical facts and explaining the 'Fast-Swiping Males' phenomenon. In Section 4, I utilize agent-based simulation methods to analyse convergence and dynamics of my model, and present a discussion on socially-efficient budget interventions. Finally, Section 5 presents concluding remarks and outlines potential avenues for future research.

1.1 Related Work

The present work draws inspiration from two key branches of economics literature: that of search and matching, which studies the decision-making process of agents who seek, for example, a job, a business partner, or a spouse, and that of mean field game theory, which models complex dynamic games involving a large number of players. I discuss each of these in turn, and then contrast this work with the handful of papers that have focused on specifically analysing SBDA market configurations.

Despite the abundance of papers within the search and matching literature, which has been amply surveyed by Chade et al. (2017), I draw focus on works that consider the three defining features of SBDA markets: decentralised matching, two-sidedness, and bilateral sequential interactions. A seminal paper at the heart of this intersection is that of Burdett and Coles (1997), which studies the marriage market for ex-ante heterogeneous agents under uniform random search, extending the work of Becker (1973) by showing that positive assortative matching can arise even in the absence of log-supermodularity. Several extensions followed this work, considering settings with idiosyncratic preferences (Burdett and Wright, 1998), noisy attractiveness observations (Chade, 2006), and even convergence onto the set of stable matchings (Adachi, 2003). These various different 'flavours' of two-sided matching models served as great inspiration for this dissertation, and the framework developed hereafter is perhaps most similar to that of Burdett and Wright (1998), with three major distinctions. Firstly, the model formulated in this paper extends the above by allowing for multiple partners within a user's lifetime, a feature which was probably not significant within the labour market context considered by Burdett and Wright (1998), but which proves quintessential given the role of SBDA's in enabling casual relationships. Furthermore, the model I present extends the above by allowing for sex-specific mass differences, as well as exogenous agent inflows; a point which was noted as a worthwhile extension by Burdett and Wright themselves, and which is fundamental in order to consider the effects of gender imbalances within the platform. Finally, the framework developed in this paper considers a discrete time framework, unlike Burdett and Wright (1998) and most other works in the matching literature. Although continuous-time models provide sharper analysis and more flexible empirical specifications (Burdett and Coles, 1999), this modelling choice lends itself naturally to the use of agent-based simulations, which are employed to asses convergence and model dynamics in a richer manner.

On the other hand, mean field game theory focuses on dynamic games with a large number of agents, for which curses of dimensionality often arise due to intractable state spaces (Maskin and Tirole, 2001). To deal with this, mean field models consider individual interactions with the *aggregate state* only,through the distributions over states and strategies within the game, rather than interactions with all other players. This abstraction is cemented with a *consistency check*, such that equilibria arises when rational play given an aggregate state maintains this same state as a fixed point. This approach, perhaps first considered by Jovanovic and Rosenthal (1988), has been successfully applied to settings such as network routing (Calderone and Sastry, 2017), dynamic auctions with learning (Iyer et al., 2014) and, perhaps most relevantly, online matching platforms (Kanoria and Saban, 2021; Immorlica et al., 2021). In this paper, I rely on mean-field assumptions to abstract from observability considerations: within SBDA's, the market-wide history is unobservable to players, and thus traditional equilibrium concepts such as Perfect Bayesian Equilibria would require beliefs over history spaces, and even beliefs over the beliefs other players may hold (a complication known as nested beliefs (Brandenburger and Dekel, 1993)). This yields two central problems: first, that equilibria become virtually impossible to compute, and, by extension, that the model assumes an unreasonable level of rationality on behalf of agents. Thus, by considering interactions with the platform state, the model presented in this paper characterizes equilibria that are both insightful and representative of real-life behaviour and dynamics.

Among the few papers that specifically consider SBDA matching markets, one that stands out is the recent work by Kanoria and Saban (2021), which postulates a two-sided dynamic matching model with vertically-differentiated agents, and finds that platforms with unbalanced markets can improve welfare by forcing the short side to propose. Furthermore, the work presented by Immorlica et al. (2021) focuses on the problem of determining a directed search algorithm in SBDA's through type-contingent meeting rates for agents. Both of these papers contain similar features within the theoretical models they develop, and these have largely influenced my work in several ways; for example, by embedding mean-field assumptions that simplify the SBDA market from a game theoretical perspective. Despite this, there are three main differences between my work and above that are worth discussing.

2 Theoretical Model

2.1 Setup

Throughout this section, I establish the theoretical framework for the model considered in this paper. Fix a non-atomic continuum of male and female agents and consider the dynamic two-sided market formed by the SBDA platform, which agents can join to search for potential romantic partners. For ease of exposition, I assume that this market is heteronormative such that male agents search exclusively for female agents and vice-versa. Time is discrete and indexed $t = 0, 1, 2, ...$ over an infinite horizon. At every time period, agents from each sex are paired and presented a candidate partner from the opposite side of the market.

We model agents with heterogeneous preferences (capturing the notion that 'beauty lies in the eye of the beholder') and thus, after being paired, each agent observes an *idiosyncratic attractiveness value* $\theta \in \Theta := [0, 1]$ for their candidate. These values are i.i.d according to a pair of absolutely continuous CDF's F_m, F_w, with corresponding PDF's f_m, f_w; female agents drawing male candidate values from F_m and vice versa. Importantly, the value men i draws for women j does not necessarily equal the value that j draws for i, and, for simplicity, these are modelled these as independent from one another.

After observing their candidate's attractiveness, agents then choose whether to swipe left (dislike) or right (like) on them, yielding an action space of $\mathcal{A} = \{\text{left}, \text{ right}\}$. If both agents swipe right on one another, they are said to have *matched* and both receive a matching payoff, however, if either agent swipes left, they both receive a payoff of zero. Contingent on swiping right on a candidate with attractiveness θ, a user earns a matching payoff $u(\theta)$, where $u(\cdot)$ is a continuous, strictly increasing function that satisfies $u(0) = 0$. This last property stems from the fact that, in Tinder, users are allowed to unmatch with each other, thus implying that matching with the least attractive individual on the other side of the market is weakly preferred to not matching.

After payoffs have been received, players are paired to different candidates and the stage interaction is repeated. Given the continuum of agents, I assume that interactions take place *anonymously* in the style of Jovanovic and Rosenthal (1988). Furthermore, to the agents' knowledge, pairings are determined in an unknown manner (since SBDA's are generally secretive regarding the algorithms used), effectively making their problem one of uniform random search.

Figure 1: Sequence of events within each time period

Perhaps trivially, swiping right in the stage interaction described above is both weakly dominant for all agents and yields a Pareto-optimal outcome, thus implying that, in a repeated interaction, the market equilibrium would have all agents exclusively swiping right. Despite this, the main selling point of SBDA's is a reduction in searching costs for individuals seeking romantic encounters, and this is only accomplished if matches have a high likelihood of resulting in real-life romantic attraction. Because of this, SBDA's like Tinder place a cap on the total number of right swipes for each user, thus enabling this as a form of costly signalling. I refer to the total number of right-swipes a user has left as its *budget*, b_t, which evolves dynamically according to the law of motion:

$$b_{t+1} = b_t - a_t$$

where the budget caps for each sex, B_m and B_w, are determined exogenously. The budget sets for men and women are thus defined by $\mathcal{B}_s = \{b \in \mathbb{Z} : 1 \leq b \leq B_s\}$, for each sex $s = m, w$. Each period, new men and women enter the platform at rates $\lambda_m, \lambda_w > 0$. Importantly, agents depart from the platform in one of two ways: they can leave *endogenously*, if they expend their swiping budget, or *exogenously* with probability $(1 - \delta)$. This admits to the interpretation of a geometrically distributed lifetime within the platform, parametrised by δ, and implies that users use this as a discounting factor for future payments.

Due to the anonymity assumption above, agents can assume that they seldom interact with the same agent more than once throughout their lifetime. This, along with the mean-field assumption established in subsection 2.2, abstracts away from history-related considerations, essentially simplifying the agent's gameplay by establishing dependency on the candidate attractiveness and their own budget only. I therefore restrict focus to stationary strategies, which are both time and history-independent, denoted by $\mu : \Theta \times \mathcal{B}_m \to \Delta\mathcal{A}_m$ for men and $\omega : \Theta \times \mathcal{B}_w \to \Delta\mathcal{A}_w$ for women, where ΔS denotes the probability simplex over set S.

2.2 The Dating Market

Given the above framework, I now outline the platform state variables that make up the SBDA market. Let $N_{mt}(b), N_{wt}(b)$ denote the mass of male and female agents (respectively) with a budget of $b \in \mathcal{B}$ in a given time period t. Furthermore, since gender imbalances can leave some agents in the long side of the market unpaired, a pairings process must be fixed. Given fairness considerations as well the automated nature of SBDA platforms, I assume an efficient matching technology and model pairings as a Bernoulli process parametrised by market tightness; thus, the probability of being paired with a candidate is defined for both sides as:

$$\tau_{mt} := \min\left\{\frac{N_{wt}}{N_{mt}}, 1\right\}, \quad \tau_{wt} := \left(\frac{N_{mt}}{N_{wt}}\right)\tau_{mt}$$

From the above, the platform state at time period t can be defined as $\Psi_t = (N_{mt}, N_{wt})$. For most of this paper, I focus on characterising user behaviour and its resulting implications in a stationary setting (which is denoted by omitted time subscripts), although some discussion of coupled strategy and market dynamics is provided in Section 4. As a necessary requirement, the market steady state $\Psi_t = \Psi_{t+1} = ... = \Psi$ must satisfy the balanced flow conditions [2] for our continuum model; these are presented below for the female agents, but they apply analogously to the male side of the market. Firstly, the entry flow of agents into the platform must equal the departure flow:

$$\lambda_w = \underbrace{(1-\delta)\sum_{b\in\mathcal{B}_w} N_w(b)}_{\text{Exogenous Outflow}} + \underbrace{N_w(1)\delta\tau_w \int_\Theta \omega(\theta, 1)\, dF_m(\theta)}_{\text{Endogenous Outflow}} \tag{2.1}$$

Secondly, for both sides, the flow of agents into any particular budget level must equal the outflow of agents from that same level. Thus, for all $b \in \mathcal{B}_w$:

$$\underbrace{N_w(b+1)\delta\tau_w \int_\Theta \omega(\theta, b+1)\, dF_m(\theta)}_{\text{Inflow into } b} = \underbrace{N_w(b)\Big[(1-\delta) + \delta\tau_w \int_\Theta \omega(\theta, b)\, dF_m(\theta)\Big]}_{\text{Outflow from } b} \tag{2.2}$$

Finally, the entry flow of agents into the platform must equal the outflow from the top budget level, hence:

[2]Formally, these conditions rely on the exact law of large numbers, which has been rigorously developed for discrete-time settings by Duffie et al. (2018), but a technical discussion of this lies outside the scope of this paper

$$\lambda_w \;=\; \underbrace{N_w(B_w)\Big[(1-\delta) \;+\; \tau_w\delta\int_\Theta \omega(\theta, B_w)\, dF_m(\theta)\Big]}_{\text{Outflow from } B_w} \tag{2.3}$$

2.3 The Search Problem

With the model framework and market dynamics outlined above, I now explore the decision problem faced by female agents in the market, with analogous results and implications for the male side. In the discussion below, I derive the female best-response function given a fixed, stationary market state Ψ and male strategy μ. To begin this analysis, consider a woman i who is paired with a man j in Tinder. The expected ex-interim payoff for this women, given that she observes attractiveness θ for candidate j and chooses action a, is the following:

$$U(\theta, a) = \Big(\overline{\mu}\,\mathbb{1}\{a = \text{right}\}\Big)\, u(\theta), \quad \text{where} \quad \overline{\mu} \;= \sum_{b\in\mathcal{B}_m}\int_\Theta \frac{N_m(b)}{N_m}\,\mu(\theta', b)\, dF_w(\theta')$$

Here, $\overline{\mu}$ denotes candidate j's strategy averaged over the possible attractiveness that he may observe for i and his possible budget level, both of which are unknown to woman i. While traditional equilibrium concepts would consider candidate j's individual behaviour and, necesarily, beliefs over his possible budget level, the payoff function above imposes a mean-field assumption such that, conditional on the platform state Ψ, woman i considers only the empirical frequency with which she receives a right-swipe. This modelling choice has been employed by Immorlica et al. (2021) and Iyer et al. (2014) among others, as it simplifies the full-fledged dynamic game by collapsing it onto a pair of Markov Decision Processes (MDP's), where strategy ω is a best response for female agents if and only if it is an optimal policy for the corresponding MDP. Let the jump times of the realized pairing process for woman i be index by k. Given that, at the time of pairing, this women has a budget of b right swipes left, she then solves the constrained MDP presented below, captured by the value function $V_w(\theta, b)$:

$$\begin{aligned} V_w(\theta, b) = \max_{\{a_k\}_{k=0}^\infty} \quad & \mathbb{E}_\theta\left[\sum_{k=0}^\infty \delta^k U(\theta_k, a_k) \mid \theta_0 = \theta, b_0 = b\right] \\ \text{s.t.} \quad & b_{k+1} = b_k - a_k \\ & b_k \in \mathcal{B}_w \cup \{0\} \\ & a_k \in \mathcal{A} \end{aligned}$$

Importantly, the first two constraints along with the exogenous departure process make this problem non-trivial; by limiting woman i's right-swiping budget, the platform imposes an opportunity cost between swiping right on man j and foregoing potential future matches with more attractive men, whilst the exogenous departure process removes the possibility of simply waiting around to swipe right on the top B_w most attractive men. By standard dynamic programming arguments, this problem can be captured by two Bellman equations; one for when j is paired and another for when she isn't:

$$V_w^P(\theta, b) = \max\Big\{ \overline{\mu}\, u(\theta) \;+\; \delta\tau_w\, \mathbb{E}_\theta\Big[V_w^P(\theta', b-1)\Big] \;+\; \delta(1-\tau)V_w^{NP}(b-1)\,, \\ \delta\tau_w\, \mathbb{E}_\theta\Big[V_w^P(\theta', b)\Big] \;+\; \delta(1-\tau_w)V_w^{NP}(b)\Big\} \tag{2.4}$$

$$V_w^{NP}(b) = \delta\tau_w\, \mathbb{E}_\theta\Big[V_w^P(\theta', b)\Big] \;+\; \delta(1-\tau_w)V_w^{NP}(b) \tag{2.5}$$

With some straightforward algebra, the above two equations can be merged into the full Bellman equation below. Note that, to impose the swiping budget constraint from the above MDP, it must be the case that $V(\theta, 0) = 0,\ \forall\theta \in \Theta$, since agents with no right-swipes left must leave the platform and can't accumulate any additional payoffs:

$$V_w(\theta, b) \;=\; \max\Big\{ \overline{\mu}\, u(\theta) + \alpha\, \mathbb{E}_\theta\Big[V_w(\theta', b-1)\Big]\,,\; \alpha\, \mathbb{E}_\theta\Big[V_w(\theta', b)\Big] \Big\} \tag{2.6}$$

Where α is the effective discount rate accounting for the exogenous possibilities of both departures and pairings, defined as:

$$\alpha := \frac{\tau_w \delta}{1 - \delta(1-\tau_w)}$$

Upon inspection, it is clear that the value function is of a piecewise nature in θ; thus, the optimal policy can be determined by a set of reservation attractiveness levels, $\{\tilde{\omega}\}_{b\in\mathcal{B}_w}$, where women j swipes right for partners who exceed the reservation level for her current budget. These reservation levels must be such that woman i is indifferent between swiping left or right, thus:

$$\omega(\theta, b) = \begin{cases} 1, & \theta \geq \widetilde{\omega}_b \\ 0, & \theta < \widetilde{\omega}_b \end{cases}\,, \quad \text{where } \widetilde{\omega}_b \text{ satisfies:}$$

$$\overline{\mu} u(\widetilde{\omega}_b) = \alpha\, \mathbb{E}_\theta\Big[\, V(\theta', b) - V(\theta', b-1)\,\Big]$$

Although reservation attractiveness levels can be computed using numerical algorithms such as value or policy iteration (Rust, 1987), they are more explicitly characterized by the result below (with a corresponding proof included in Appendix A):

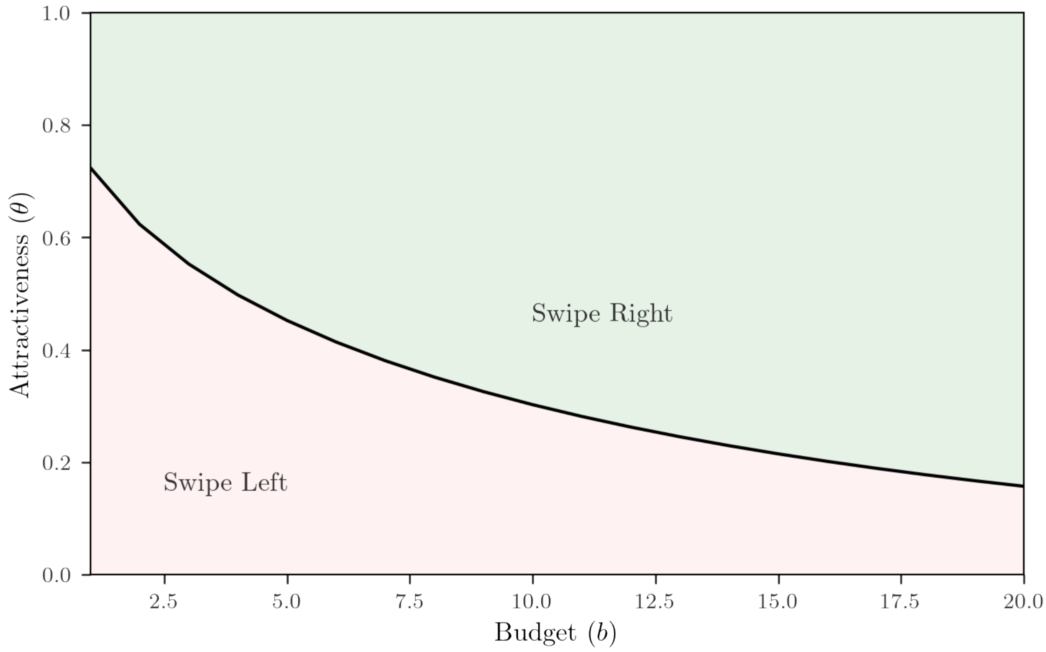
Proposition 1. *The set of reservation attractiveness levels for women, $\{\tilde{\omega}_b\}_{b\in\mathcal{B}_w}$, uniquely satisfies the recurrence relation and initial condition below, over the budget set $\mathcal{B}_w$:*

$$u(\widetilde{\omega}_b) \;=\; \alpha u(\widetilde{\omega}_b)F_m(\widetilde{\omega}_b) \;+\; \alpha u(\widetilde{\omega}_{b-1})\Big[1 - F_m(\widetilde{\omega}_{b-1})\Big] \;+\; \int_{\widetilde{\omega}_b}^{\widetilde{\omega}_{b-1}} \alpha u(\theta')\, dF_m(\theta') \tag{2.7}$$

$$u(\widetilde{\omega}_1) \;=\; \alpha u(\widetilde{\omega}_1)F(\widetilde{\omega}_1) \;+\; \alpha \int_{\widetilde{\omega}_1}^{1} u(\theta') dF(\theta') \tag{2.8}$$

By further inspecting this result, it is evident that the aggregate behaviour of the opposite side of the market ($\overline{\mu}$) has no direct influence over female best responses. Instead, this influence happens indirectly through the steady state masses and their effect on

Figure 2: The Optimal Swiping Rule



how agents discount inter-temporal payoffs through α. Using the recurrence relation in Proposition 1, the agent-best response was computed for an arbitrary set of exogenous parameters, with results shown in Figure 2. As evidenced by these, the optimal policy (and best-response function) for agents is marked by a clear cut-off rule for swiping right. These cut-off values are decreasing in the agent's budget, which captures the notion that an agent's current swipe is more valuable than all preceding ones given the increasing opportunity cost.

3 Equilibrium & Comparative Statics

3.1 Steady State Equilibrium and Approximation

Using the framework and results above, I now present a refined definition for the steady state equilibrium of the market:

Definition 1. *A Steady State Equilibrium is defined by a triplet* $(\mu^*, \omega^*, \Psi^*)$ *such that:*

1. $\mu^*(\theta, b)$ *attains* $V_m(\theta, b)$, $\forall\, \theta, b \in \Theta \times \mathcal{B}_m$, *given* ω^*, Ψ^*

2. $\omega^*(\theta, b)$ *attains* $V_w(\theta, b)$, $\forall\, \theta, b \in \Theta \times \mathcal{B}_w$, *given* μ^*, Ψ^*

3. Ψ^* *satisfies Equations 2.1, 2.2, and 2.3 given the strategy profile* (μ^*, ω^*)

Intuitively, the above definition establishes two conditions that must be satisfied by an equilibrium market configuration. Firstly, it must be the case that μ^* and ω^* are mutual best responses given the platform state Ψ^* for which, as previously outlined, a necessary and sufficient condition would have them each solve the sex-specific MDP. In this sense, the above equilibrium concept demands *partially rational expectations* (PRE) from agents, as per Burdett and Coles (1997), since it requires agents to play according to utility-maximising strategies, imposing rationality on all aspects of the game other than the platform state dynamics. Furthermore, in line with mean-field game theory literature, a *consistency check* is imposed by the third condition, which requires that the platform steady state to which agents are best-responding with (μ^*, ω^*) is sustained as a fixed point, thus confirming a PREE (Burdett and Coles, 1997) as a full steady state equilibrium.

Although formal proofs for the existence and uniqueness of steady-state equilibria are outside the scope of this paper, I instead rely on computational procedures[3] to approximate equilibria under various exogenous settings to shed some light on the insights provided by the above theoretical model. I propose two computational procedures to solve for model equilibria, both of which involve framing the recurrence relation presented in Proposition 1, as well as Equations 2.1, 2.2, and 2.3, as a system of $2(|\mathcal{B}_m| + |\mathcal{B}_w| + 1)$ non-linear equations, denoted by $\mathbf{E}(\mu, \omega, \Psi)$. From here, the first procedure utilizes a modified version of Powell's method, as per the MINPACK 1 routine (Moré et al., 1980), whilst the second one solves the following least squares problem:

$$\mu^*, \omega^*, \Psi^* = \arg\min_{\mu,\omega,\Psi} \quad ||\mathbf{E}(\mu, \omega, \Psi)||^2 \quad \text{s.t.} \quad \mu, \omega \in [0, 1]$$

3.2 Best Response Analysis

Using the computational procedures outlined above, a number of insights can be uncovered related to how exogenous parameters affect an agent's best-response swiping strategy. The first parameter I analyse is the discount factor, which represents the probability of remaining inside the platform for an additional time period, but is often interpreted as the representative agent's patience level. To determine the effects of changes in the discount factor, I computed the best-response policy over a range of different values for δ (using an arbitrary set of exogenous parameters), with results shown in Figure 3. Evidently, as the agent becomes less patient, they 'lower their standards' for potential matches in the platform, shifting their swiping curve downwards.

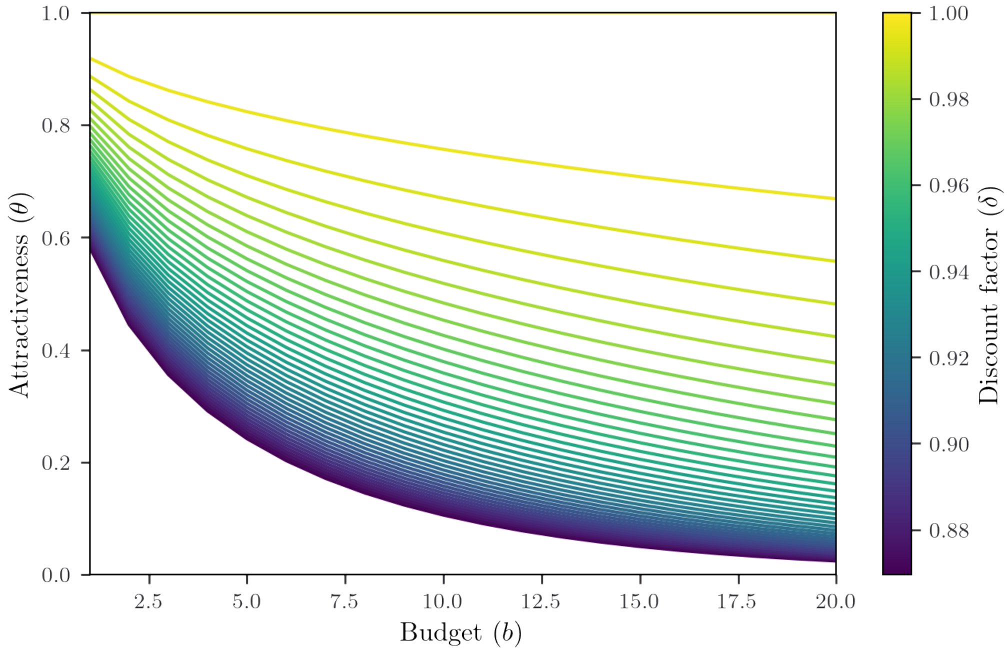
Another interesting parameter to examine is the absolute risk aversion of agents, which I choose to interpret as their 'desperateness' for matching. In the platform, risk-averse agents prefer a higher chance of matching (even if these yield relatively lower payoffs), whilst risk-loving agents prefer to wait around and save their swipes for high-yield candidates. To perform comparative statics on this parameter, I fix a CARA utility function for agents, with parameter r corresponding to the Arrow-Pratt coefficient for absolute risk aversion. I then compute the optimal swiping rule for various different values of r, with results for this shown on Figure 4. From here, it is evident that as agents become 'more desperate' for matches, implied by rising absolute risk aversion, they lower their standards for right-swiping on a candidate, thus shifting their swiping curve downwards.

3.3 Market Configuration Analysis

Finally, I perform comparative statics at the platform level to determine how different factors affect market configurations. This is especially important as it considers not only

[3]The code required to reproduce all analysis presented in this paper is fully accessible under the GitHub repository `patohdzs/project-tinder`

Figure 3: Comparative Statics on the Discount Factor

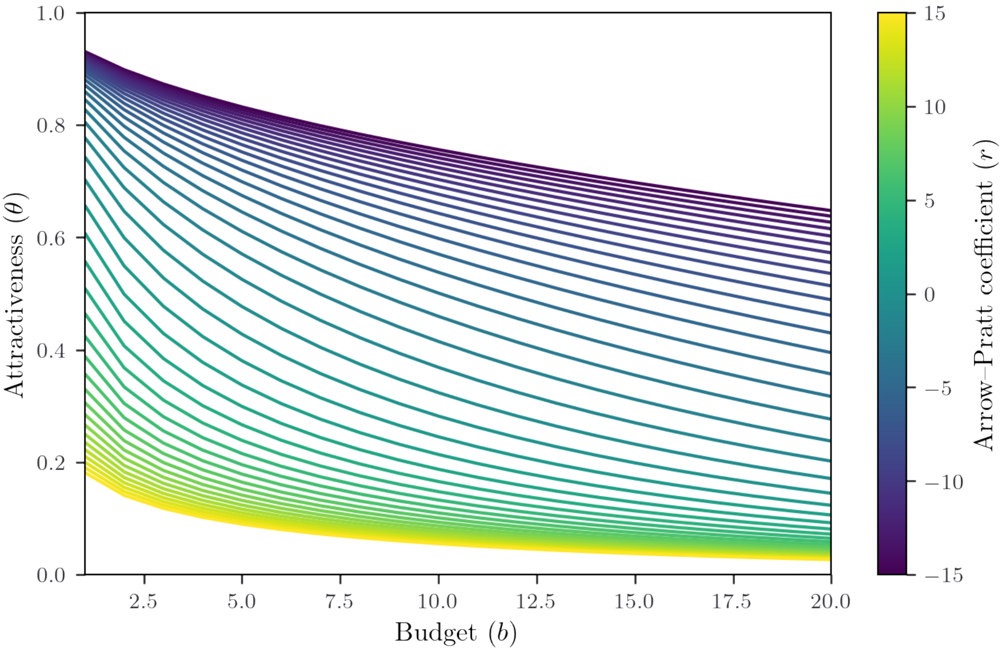


the effects on best-responses for one sex, but also how these propagate across the market through its aggregate state. More specifically, I focus the aforementioned 'Fast-Swiping Males' puzzle, investigating the discrepancy in swiping rates and matching outcomes between men and women, and I present two possible explanations for how the model developed in this paper can replicate and explain this outcome. The first of these concerns differential agent inflows between men and women, which occur exogenously within my model but are in line with empirical findings, which place. To asses the market configurations arising from of this situation, I compute the model equilibria under a 6:1 ratio between arrival rates λ_m and λ_w. The results for this are shown in Figure 5, highlighting three main insights for this scenario.

Firstly, under the above scenario, the steady-state mass of male agents in the platform is around ten times greater than that of female agents (in line with empirical estimates), implying that male agents face a tight market and struggle to get paired with female candidates. This is further evidenced by the top-center plot within Figure 5, which shows that male agents are highly concentrated in the top budget levels. Due to the effect of market tightness on the effective discount rate, male agents are also more impatient than women on the platform, which makes sense intuitively as they also face considerably worse matching odds. This effect is captured by their best-response strategy, which sits considerably lower than the female swiping curve, effectively showing how a congested market lowers male patience and by extension, their standards, leading them to swipe right on most women. Ultimately, this explains the 'Fast-Swiping Males' puzzle given that, under this particular equilibrium, men receive right-swipes with probability $\overline{\omega} = 0.491$, compared to $\overline{\mu} = 0.988$ for women, thus replicating the observed phenomenon through a traceable shock on agent inflows.

4 Agent-Based Simulations

Figure 4: Comparative Statics on Absolute Risk Aversion

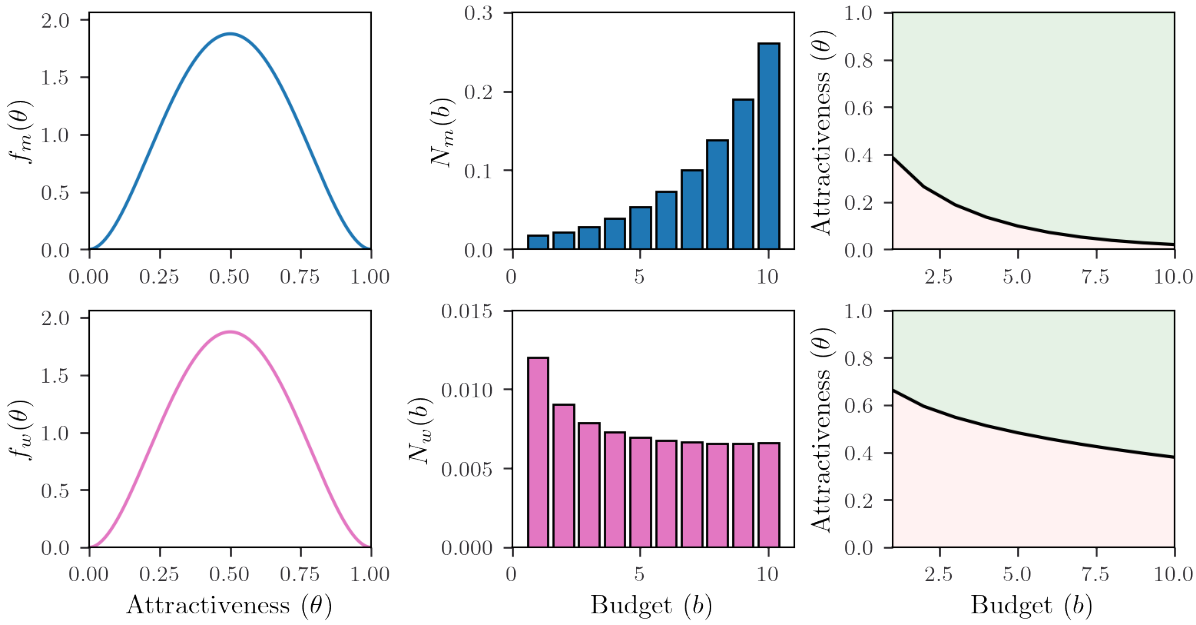


4.1 Convergence and Dynamics

Given the lack of accessible SBDA user data, I developed on agent-based simulation environment to explore the evolution of both behavioural and market-level dynamics under the above theoretical foundations. Agent-based modelling (ABM) aims to explore "how macro phenomena emerges from micro level behaviour among a heterogeneous set of interacting agents" (Janssen, 2005). In essence, this methodology aims to study complex dynamical processes through computational simulations, as opposed to determining closed-form solutions for these through heavily simplified assumptions, which can sometimes result in large differences between predicted and real-life trajectories for complex systems (such as markets). When applied in combination with a micro-founded theoretical model, ABM can provide powerful insights by aiding in the identification of equilibrium states, which can be computationally expensive to approximate (and in some cases even non-existent).

To start, I explored the convergence and stability of the SBDA market under various arbitrary exogenous configurations. In particular, Figure 6 shows the simulated evolution of (sex-specific) agent masses over 300 time periods, with a 2:1 ratio between male and female arrival flows. As evident from these results, the computational procedures in subsection 3.1 are able to correctly predict the steady state market masses; furthermore, the ABM simulations show that the long side of the market (males) takes considerably longer to converge onto its steady-state level. One technical point worth noting is that, due to the inability of computational simulations in handling non-discrete structures, the above simulations depict *agent stocks* as opposed to *agent masses*, as per our continuum model. Thus, because agent departures and pairings follow random processes, the above equilibrium acts as a *stochastic steady state*, with convergence occurring in the stationary sense rather than in typical deterministic fashion. Nevertheless, I examine the limiting case of these dynamics, with Figure 7 depicting how, by the law of large numbers, stationary deviations around the steady state equilibrium level become negligible as the agent

Figure 5: Market Configuration Under Differential Agent Inflows



stocks tend to infinity.

4.2 Social Efficiency

5 Conclusion

Overall,

5.1 Future Work

There are several interesting avenues for future research concerning SBDA matching platforms. Firstly, although I present a proof for the existence and uniqueness of agent best-responses,

Firstly, more work could be done to explore alternative dynamics behind these platforms, both through ABM but

- Evolutionary dynamics? - Mixed preferences... - Model that allows for both multiple casual matches and long-term partneships, after which agents leave the market

Figure 6: Agent-Based Simulation Convergence

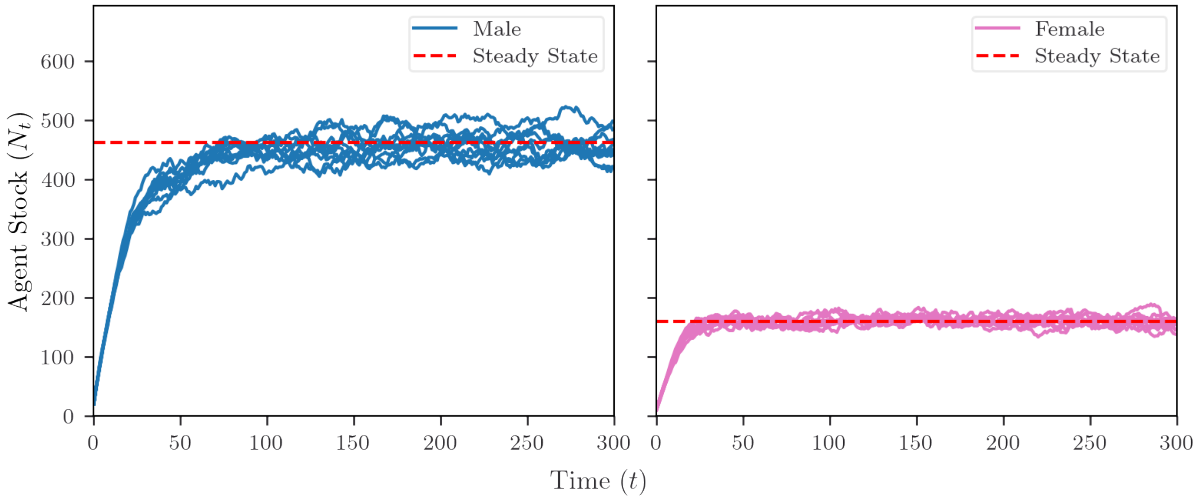
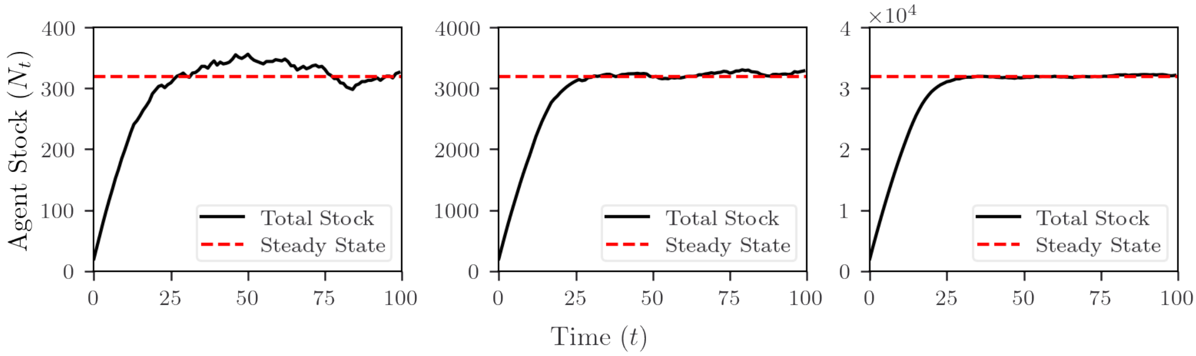


Figure 7: Agent-Based Simulation Convergence with Varying Sample Sizes



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A Proof for Proposition 1

Proof. To prove Proposition 1, we rely the following two equations; the first of which expresses the agent's value function in piecewise form, and the second of which describes the necessary condition for all reservation attractiveness values:

$$V(\theta, b) = \begin{cases} \overline{\mu} u(\theta) + \alpha\, \mathbb{E}_\theta \Big[V(\theta', b-1) \Big], & \theta > \widetilde{\omega}_b \\ \alpha\, \mathbb{E}_\theta \Big[V(\theta', b) \Big], & \theta \leq \widetilde{\omega}_b \end{cases} \tag{A.1}$$

$$\overline{\mu} u(\widetilde{\omega}_b) = \alpha\, \mathbb{E}_\theta \Big[\, V(\theta', b) - V(\theta', b-1) \,\Big] \tag{A.2}$$

To simplify notation, denote the continuation value at budget b by:

$$K_b := \alpha\, \mathbb{E}_\theta \left[V(\theta', b) \right]$$

Starting out with Equation A.2 and expanding out the expectation operator, we can use A.1 to substitute in the piecewise definitions of $V(\theta, b)$ over the appropriate intervals:

$$\begin{aligned} \overline{\mu} u(\widetilde{\omega}_b) &= \alpha \int_0^1 V(\theta', b) - V(\theta', b-1)\, dF_m(\theta') \\ &= \alpha \int_0^{\widetilde{\omega}_b} K_b\, dF_m(\theta') \;+\; \alpha \int_{\widetilde{\omega}_b}^1 \overline{\mu} u(\theta') + K_{b-1}\, dF_m(\theta') \\ &\quad - \;\alpha \int_0^{\widetilde{\omega}_{b-1}} K_{b-1}\, dF_m(\theta') \;-\; \alpha \int_{\widetilde{\omega}_{b-1}}^1 \overline{\mu} u(\theta') + K_{b-2}\, dF_m(\theta') \end{aligned} \tag{A.3}$$

Furthermore, Equation A.2 implies that:

$$\overline{\mu} u(\widetilde{\omega}_b) + K_{b-1} = K_b$$

$$\overline{\mu} u(\widetilde{\omega}_{b-1}) + K_{b-2} = K_{b-1}$$

Then, by substituting these expressions into A.3, we arrive at A.4:

$$\begin{aligned} \overline{\mu} u(\widetilde{\omega}_b) = \alpha \int_0^{\widetilde{\omega}_b} \overline{\mu} u(\widetilde{\omega}_b) + K_{b-1}\, dF_m(\theta') \;+\; \alpha \int_{\widetilde{\omega}_b}^1 \overline{\mu} u(\theta') + K_{b-1}\, dF_m(\theta') \\ - \;\alpha \int_0^{\widetilde{\omega}_{b-1}} K_{b-1}\, dF_m(\theta') \;-\; \alpha \int_{\widetilde{\omega}_{b-1}}^1 \overline{\mu} u(\theta') + K_{b-1} - \overline{\mu} u(\widetilde{\omega}_{b-1})\, dF_m(\theta') \end{aligned} \tag{A.4}$$

With some algebra, this simplifies down to the recurrence relation in Equation 2.7:

$$u(\widetilde{\omega}_b) = \alpha u(\widetilde{\omega}_b) F_m(\widetilde{\omega}_b) \;+\; \alpha u(\widetilde{\omega}_{b-1}) \Big[1 - F_m(\widetilde{\omega}_{b-1}) \Big] \;+\; \alpha \int_{\widetilde{\omega}_b}^{\widetilde{\omega}_{b-1}} u(\theta')\, dF_m(\theta') \tag{A.5}$$

Furthermore, to obtain the initial condition for the above, note that the right-swiping budget constraint imposes $V(\theta, 0) = 0, \forall b \in \mathcal{B}_w$. Then, A.1 and A.2 simplify to:

$$V(\theta, 1) = \begin{cases} \overline{\mu} u(\theta), & \theta > \widetilde{\omega}_1 \\ \alpha\, \mathbb{E}_\theta \Big[V(\theta', 1) \Big], & \theta \leq \widetilde{\omega}_1 \end{cases} \tag{A.6}$$

$$\overline{\mu} u(\widetilde{\omega}_1) = \alpha\, \mathbb{E}_\theta \Big[\, V(\theta', 1) \,\Big] \tag{A.7}$$

Beginning with A.7, we simplify until arriving at Equation 2.8:

$$\begin{aligned} \overline{\mu} u(\widetilde{\omega}_1) &= \alpha\, \mathbb{E}_\theta \Big[\, V(\theta', 1) \,\Big] \\ &= \alpha \int_0^{\widetilde{\omega}_1} K_1\, dF_m(\theta') + \alpha \int_{\widetilde{\omega}_1}^1 \overline{\mu} u(\theta')\, dF_m(\theta') \\ &= \alpha \int_0^{\widetilde{\omega}_1} \overline{\mu} u(\widetilde{\omega}_1)\, dF_m(\theta') + \alpha \int_{\widetilde{\omega}_1}^1 \overline{\mu} u(\theta')\, dF_m(\theta') \\ &= \alpha \overline{\mu} u(\widetilde{\omega}_1) F_m(\widetilde{\omega}_1) + \alpha \int_{\widetilde{\omega}_1}^1 \overline{\mu} u(\theta')\, dF_m(\theta') \\ \implies u(\widetilde{\omega}_1) &= \alpha u(\widetilde{\omega}_1) F_m(\widetilde{\omega}_1) + \alpha \int_{\widetilde{\omega}_1}^1 u(\theta')\, dF_m(\theta') \end{aligned}$$

To conclude the proof, note that the existence and uniqueness of some $\widetilde{\omega}_b$ that satisfies A.2 is guaranteed given the assumptions on $u(\theta)$ being continuous and strictly increasing. Since the difference between any two consecutive continuation values must lie strictly between 0 and $u(1)$, then, by the Intermediate Value Theorem, there exists one and only one root $\widetilde{\omega}_b$ satisfying A.2 and, by extension the above reoccurrence relation. $\square$